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# Are Haar-like Rectangular Features for Biometric Recognition Reducible?

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**Abstract.** Biometric recognition is still a very difficult task in real-world scenarios wherein unforeseen changes in degradations factors like noise, occlusion, blurriness and illumination can drastically affect the extracted features from the biometric signals. Very recently Haar-like rectangular features which have usually been used for object detection were introduced for biometric recognition resulting in systems that are robust against most of the mentioned degradations [9]. The problem with these features is that one can define many different such features for a given biometric signal and it is not clear whether all of these features are required for the actual recognition or not. This is exactly what we are dealing with in this paper: How can an initial set of Haar-like rectangular features, that have been used for biometric recognition, be reduced to a set of most influential features? This paper proposes total sensitivity analysis about the mean for this purpose for two different biometric traits, iris and face. Experimental results on multiple public databases show the superiority of the proposed system, using the found influential features, compared to state-of-the-art biometric recognition systems.

## 1 Introduction

Biometric recognition, the identification of people based on their biological and/or behavioral characteristics like face, ear, iris, fingerprint, finger vein patterns, hand vein pattern, hand geometry, and gait, is nowadays being used in many real-world applications from security and surveillance systems, to human-computer interaction systems, to gaming, to name a few. Biometric recognition is still a challenging task as the acquired biometric signals (visual signals in this paper) are usually affected by degradation factors like noise corruption, illumination, blurriness, and occlusion. Furthermore, for contactless biometrics (like face, iris, and ear) for which there is a distance between the sensor and subject of interest, the resolution of the acquired image is another important challenge.

Several biometric recognition systems have been developed for dealing with the aforementioned challenges. These methods can be generally divided into two groups: appearance based and feature based. The appearance based algorithms use the grayscale values of the input images directly, while the feature based systems extract some features from the grayscale values and then use these extracted features for the actual recognition. In this paper we focus on two biometric traits, face and iris, but the discussion can be extended to other traits easily. Several features based approaches can be found in the literature for the chosen biometrics. For example for face recognition in [17] local texture features, in [11] local directional number patterns, and in [10] local gradient information are used. For feature based iris recognition systems for example in [19] Gabor filters, in [16] Scale Invariant Feature Transform (SIFT), and in [13] wavelets have been used. Known appearance based methods include, but not limited to, Principal Component Analysis (PCA)-based methods, Independent Component Analysis (ICA) algorithms, Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and Neural Networks (NN), to name a few. These classifiers have been well applied to the chosen biometrics of this paper. For example for face recognition PCA in [14], LDA in [3], SVM in [5], ICA in [2] and more recently Sparse Representation (SR) based methods in [8] have been used. For iris recognition a Probabilistic NN (PNN) in [19] and an LDA classifier in [21] have been used. The problem with the appearance based algorithms is that they usually need to register the input images to a fixed frame. This means that these methods mostly are sensitive to registration errors. The problem with the feature based methods is that their performance is directly depended on the effectiveness and robustness of the employed features. Furthermore, the performance of both groups of algorithms degrades when the input images are noisy, occluded by some obstacles, of low resolution, and not properly illuminated.

In our very recent work [9] a feature based approach for biometric recognition has been introduced which is shown to be robust against most degradations and poor imaging conditions. The employed features in this system [9] are Haar-like rectangular features that are extracted from integral images. These features are fed to a PNN classifier in [9] for the final recognition. The Haar-like rectangular features were first introduced for rapid and robust object detection using a boosted cascade of simple weak classifiers [15] and have usually been used for the same purpose in the literature (see [9] for more information). The problem with Haar-like rectangular features is that one can define many different such features for a given image, while only few of these features are useful for the actual recognition and the rest just impose extra computations to the system. This varies from a biometric trait to another one. Finding proper sets of Haar-like rectangular features from an initial set of such features is the exact concern of this paper. To do so, the proposed system introduces the Total Sensitivity Analysis (TSA) about the mean, which is further explained later in this paper.

The rest of the paper is organized as follows: biometric recognition using the Haar-like rectangular features of [9] is briefly revisited in the next section, then, TSA about the mean is explained in section 3, experimental results are discussed in section 4, and finally the paper is concluded in section 5.

## 2 Biometric Recognition using Haar-like Features

The Haar-like rectangular features are obtained by filters composing of two types of regions: white and black regions (see Figure 1). The common way for generating these filters is to consecutively divide the entire area of the filter to 2, 3, ..., $N$ regions [1]. Then, paint these regions to black or white. This can result in many such filters, which some of them, for $N = 20$, are shown in Fig. 1.

**Fig. 1.** The initial set of Haar-like rectangular filters. The index of the top-left filter is 1 and the one in the right-bottom is 115 (those in between change accordingly).

For calculating the value of a specific Haar-like rectangular feature from a given image, first, the filter is resized to the same size as the input image (without changing the relative size of its black and white regions). Then, the filter is lied on the input image such that the four corners of the filter lie on the four corners of the input image. Then, the summation of those pixel values of the input image that lie in the black region of the Haar-like rectangular filter is subtracted from the summation of those pixel values of the input image that lie in the white region of the filter. To reduce the computational time these features are usually calculated from the integral counterparts of the input image [15].

Having extracted the Haar-like rectangular features of Fig. 1 from the integral image of the input biometric, they are fed to a PNN classifier in [9]. PNN performs the recognition by finding the Probability Distribution Functions (PDF)s of the involved classes using a Parzen window like:

$$f_j(s) = \frac{1}{\sigma_j n_j} \sum_{k=1}^{n_j} W(\frac{||s - s_{kj}||^2}{\sigma_j}) \tag{1}$$

where $f_j$ is the PDF of the $j$th class, $n_j$ is the number of the samples of this class, $\sigma_j$ is a smoothing parameter, $s_{kj}$ contains the features of the $k$th training sample of the $j$th class, $s$ contains the features of the unknown sample, and $W$ is a weighting function. In PNN, $W$ is replaced by an exponential function to use PDFs of Gaussian form (see [12], and [9] for more information on PNN).

## 3 Total Sensitivity Analysis About The Mean

Having explained the Haar-like rectangular features and the employed classifier, in this section TSA is elaborated. Sensitivity analysis is a technique for finding the importance and the influence of the input features to the system [18]. Let's assume that we have a recognition system which takes $A$ features (here all the features shown in Fig. 1) as input to distinguish between $B$ different classes. Having trained the recognition system using the training samples (which are separated from the testing samples), the classical sensitivity analysis about the mean works as follows: first, all the $A$ features of system are extracted for all the testing samples. Then, for $i = 1...A$ fix the values of all the features except the

$i$th one to their mean values. Then, change the value of the $i$th feature between $\pm\sigma$ where $\sigma$ is the standard deviation of this feature. Each time that the value of the $i$th feature is changing, a new set of testing samples is generated which is used for testing the system. During the testing of the system the recognition rates of the system for each individual class are monitored. If changing the value of $i$th feature results in changing the recognition rate of the system for class $b \in B$ , the $i$th feature is considered as an influential feature for recognition of this class.

The classical sensitivity analysis measures the sensitivity of each input feature in recognizing each individual class in a given data. This however can not directly be used as a measure for monitoring the overall recognition rate of the system as improving the recognition rate of the system for one specific class may result in reducing the recognition rate of the system for another class. Therefore, the proposed system introduces the TSA as follows: for each input feature TSA is simply obtained by summing up the results of the classical sensitivity analysis for all the involved classes. It is obvious that TSA of a specific feature increases if changing the value of this feature results in improvement of the recognition rate of the system for a larger number of classes.

Having obtained the results of TSA for all the features, a threshold like $T$ can be found such that any feature with a TSA value larger than $T$ can be considered as an influential feature. The set of the influential features, $F$, is a set of features by which the recognition rate of the system is the same as the recognition rate of the system with the original set of features. It means the rest of the features that have TSA values below $T$ are actually non-contributive features. The exact value of $T$ depends on the employed traits and changes from one trait to another one and can be found experientially. The set of the sensitive features and $T$ change also from a trait's database to another database of the same trait. But there is a good similarity between the sensitive features of one trait from one database to another database of the same trait. It is shown in the experimental results that removing the non-contributive features not only gives higher recognition rates, but it results in a faster system.

## 4 Experimental Results

To show the efficiency of the employed TSA method in discarding the non-contributive features and hence finding the most influential features, multiple public databases of the two biometric traits, iris and face, have been employed. The iris database (ID) has been taken from [7]. This database contains 2240 iris images of 224 subjects each providing 10 grayscale iris images. These images are of size 320×240 pixels (Fig. 2). Four public databases have been employed for face recognition: ORL [22], UMIST [24], Faces94 [23], and Extended YaleB [4]. The number of the images in these databases are 400, 564, 3060, and 16128 images of 40, 20, 153, and 28 subjects, respectively. The sizes of the images are 92×112, 92×112, 105×120, and 168×192 pixels, respectively. These images contain variations in head-pose, expression, and illumination conditions (Fig. 2).

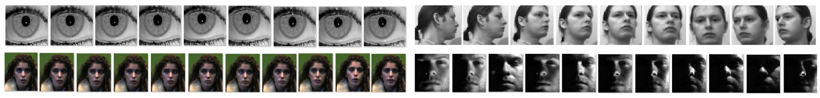

**Fig. 2.** Some samples of four of the employed databases, from top, clockwise: ID, UMIST, Extended YaleB, and faces94 databases.

The reported results in this section are obtained when the available databases are divided randomly to three parts for training, cross-validation, and testing. The sizes of each of these portions are 60%, 15%, and 25% of the entire database, respectively. The degradation in the performance of the classifier when the sizes of these three parts change is studied in [9].

The proposed system has gone through three experiments. In the first experiment, for each individual database the recognition rate of the proposed system is compared against the state-of-the-art systems when the proposed system is trained using the entire set of the extracted Haar-like rectangular features (shown in Fig. 1). The results are shown in Fig. 3. In this figure, the results of the proposed system (PS) for iris are compared against S1-S4 which are decision tree-based, appearance based PNN, SVM, and fuzzy binary decision tree-based classifiers, respectively [6]. The results for face are compared against PCA [14], LDA [3], SVM [5], ICA [2], Local Binary Patterns (LBP), and some very recent Sparse Representation (SR) based methods, DDSR, FDDL, RPCA. The results of these methods on ORL, UMIST, and YaleB are reported in [8]. It should be mentioned that some of these methods like PCA, ICA and LDA are also based on feature reduction concept.

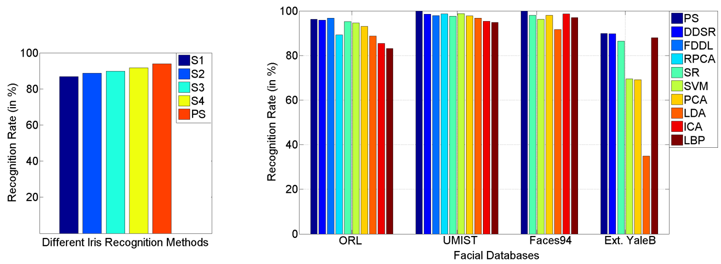


**Fig. 3.** The recognition rate of the proposed system against: (left) state-of-the-art iris recognition algorithms using ID database and (right) state-of-the-art face recognition algorithms using ORL, UMIST, Faces94, and Extended YaleB databases.

In the second experiment the explained TSA method (section 3) is applied to the entire feature set to find the most influential features and discard the non-contributive ones. To do so, for each database we define a set of most influential features, $F$, which is initially empty. Having obtained the TSA values of all the

Haar-like rectangular features, we keep adding features to $F$ based on their TSA values in a descending order. Every time a new influential feature is added to $F$, the employed PNN is trained and tested (The training and testing samples are kept separate from each other). This process continues until the recognition rate of the proposed system using $F$ is the same (within $\pm$ 0.005) as the recognition rate of the proposed system using the entire set of the Haar-like rectangular features. The results of applying TSA to four of the employed databases using the initial set of features are shown in Fig. 4. The second experiment reduces these initial sets of features to the 44, 30, 39, 41, and 44 most influential features for ID, ORL, UMIST, Faces94, and Extended YaleB databases, respectively. It means that for each of these databases only these numbers of top influential features are enough for achieving the same recognition rate as the case where the entire Haar-like rectangular features are used.

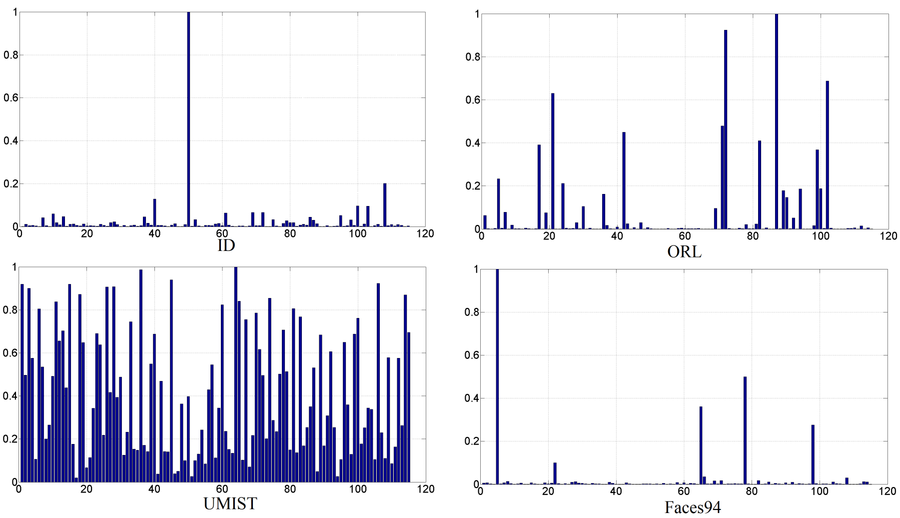


**Fig. 4.** The normalized results of the employed TSA method applied to the Haar-like rectangular features obtained from four of the employed databases. The $x$ axis in a) and b) represents the name of the Haar-like rectangular features from Fig. 1.

Though the set of the most influential features of the facial databases (the features with highest TSA value in Fig. 4) changes from one database to another one, it can be seen from Fig. 4 that the most influential features of one of the databases is usually among the top influential features of the other ones. It may seem as a drawback for the employed TSA method that the most influential features of these databases are not completely the same. But this actually makes sense as the images of these databases are captured under very different imaging conditions (Fig. 2. For example, ORL images are well focused, UMIST images have wide head poses, Faces94 images are not of good quality in terms of illumination, and Extended YaleB images mostly suffer from directional illumination). The interesting point is that regardless of the content of the database the set of possible Haar-like rectangular features that can be extracted from the database can be summarized to a set of influential features like $F$.

The third and last experiment compares the computational time of the proposed system against the systems of [9]. This timing information is shown in Fig. 5. It is obvious from this figure and Fig. 3 that beside achieving the same recognition rates of [9] the proposed system works faster.

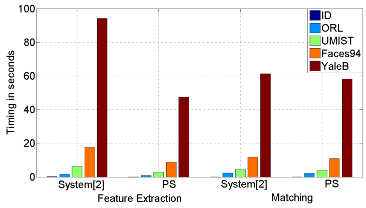


**Fig. 5.** Timing comparison of the proposed system against [9].

## 5 Conclusion

This paper proposes a biometric recognition system using Haar-like rectangular features which mostly have been used for object detection. The set of these features has proved to result in high recognition performance, but the problem is that this set may contain many different number of features while only few of them contribute to the actual recognition and the rest of the features are non-contributive. For finding and discarding the non-contributive features this paper uses total sensitivity analysis about the mean. Experimental results on two types of biometric traits, iris and face, show that total sensitivity analysis can find these most influential features which can result in a fast and reliable biometric recognition system.

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